

# Bayesian Model for Sources Intensities

Lazhi Wang

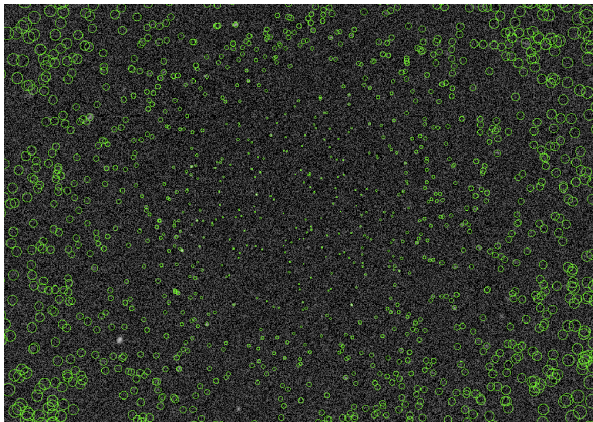
Statistics Department, Harvard University

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- 1 Background and goals of the project
- 2 Hierarchical Bayesian model
- 3 Frequency properties of the model via extensive simulation studies
- 4 Testing the existence of dark sources:
  - Calculation of test-statistic and posterior predictive p-value
  - Frequency properties of the  $ppp$  via simulation study
- 5 Real Data Application

# Data

- $Y_i$ , background contaminated photon count in a source region over a period of time  $\mathcal{T}$ .
- $X$ , photon count in the exposure of pure background over  $\mathcal{T}$ .



# Goals of the Project

- 1 To develop a fully Bayesian model to infer the **distribution of the brightness (luminosity function)** of all the sources in a population.

# Goals of the Project

- ① To develop a fully Bayesian model to infer the **distribution of the brightness (luminosity function)** of all the sources in a population.
- ② To identify the existence of **“X-ray” dark sources** in the population.
  - **“X-ray” dark sources**: sources that do not generate X-rays.

# Basic Hierarchical Bayesian Model

- Level I:

$$\begin{aligned} Y_i &= S_i + B_i \\ S_i | \lambda_i &\sim \text{Poisson}(r_i e_i T \lambda_i) \\ B_i | \xi &\sim \text{Poisson}(a_i T \xi) \\ X | \xi &\sim \text{Poisson}(A_b T \xi) \end{aligned}$$

- $S_i$  (counts): number of photons from source  $i$  in the source region,
- $B_i$  (counts): number of photons from the background in the source region,
- $\lambda_i$  (counts/s/cm<sup>2</sup>): the intensity of source  $i$ ,
- $\xi$  (counts/s/pixels): the intensity of background,
- $t$  (seconds): exposure time,
- $e_j$  (cm<sup>2</sup>): the telescope effective area,
- $r_i$ : proportion of photons from source  $i$  expected to fall in source region,
- $a_j$  (pixels): the size of source region  $i$ ,
- $A_b$  (pixels): the size of background region.

$S_i, B_i, \lambda_i, \xi$  are all unobserved/latent,  $t, e_j, r_j, a_j, A_b$  are all known constant.  $Y_j, X$  are observed data.

# Basic Hierarchical Bayesian Model

- Level II:

$$\xi \sim \text{Gamma}[\mu_0, \theta_0]$$

$$\lambda_i | \mu, \theta, \pi_d \begin{cases} = 0 & \text{with probability } \pi_d, \\ \sim \text{Gamma}[\mu, \theta] & \text{with probability } 1 - \pi_d. \end{cases}$$

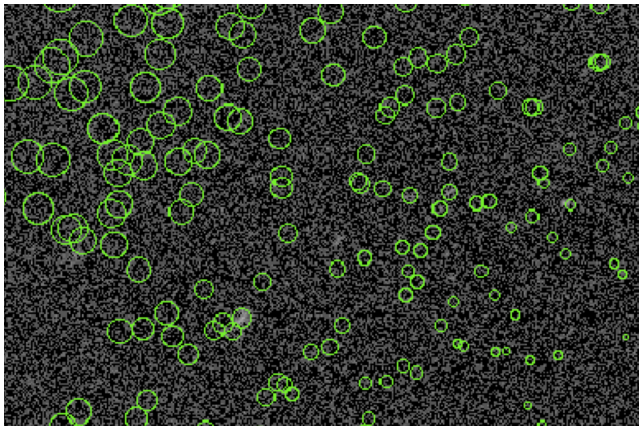
- Level III: Prior on the hyper-parameters  $\pi_d, \mu, \theta$

$$\pi_d \sim \text{Unif}(0, 1)$$

$$P(\mu, \theta) \propto \frac{1}{c_1^2 + (\mu - c_2)^2} \frac{1}{c_3^2 + (\theta - c_4)^2} I_{\mu > 0, \theta > 0},$$

# Model Extension I: Overlapping Sources

- Some source regions overlap.





# Model Extension I: Overlapping Sources

- Notation:

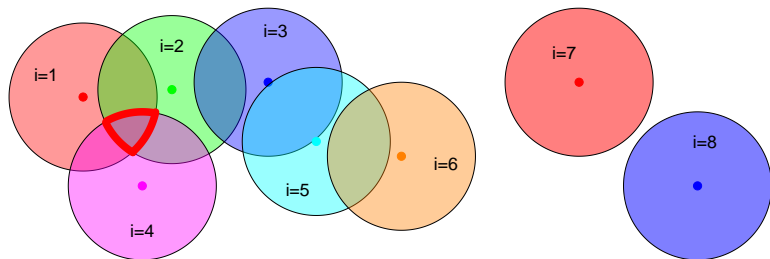
- $s$  is the set of indices of source regions that defines the segment. For example, the highlighted segment is  $s = \{1, 2, 4\}$ .

- Level I model:

$$Y_s = S_s + B_s = \sum_{i \in s} S_{s,i} + B_s,$$

$$S_{s,i} | \lambda_i \sim \text{Poisson}(r_{s,i} e_s T \lambda_i)$$

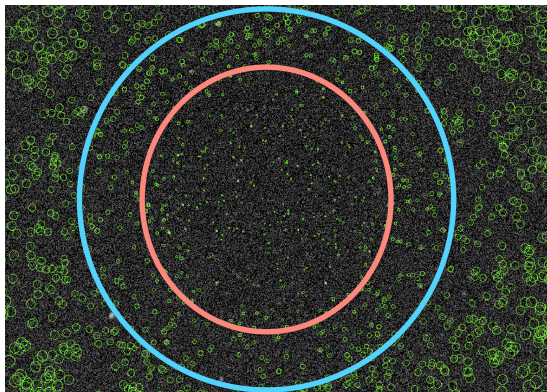
$$B_s | \xi \sim \text{Poisson}(a_s T \xi)$$



## Model Extension II: Different Background Intensities

- In our data, the background intensity has **an increasing trend** from the center to the edge of the telescope.

Projected Angle (arcmin)	0-6	6-8	8-16
Intensity (counts/pixels)	0.0010	0.0104	0.0108



# Model Extension II: Different Background Intensities

- Notation:

- $X_k$  (counts): number of photons collected in background region  $k$  over  $T$  seconds
- $\xi_k$  (counts/s/pixels): the background intensity in regions  $k$
- $A_k$  (pixels): the size of background region  $k$
- $\mathcal{R}_k$ : the collection of source segments in the background region  $k$

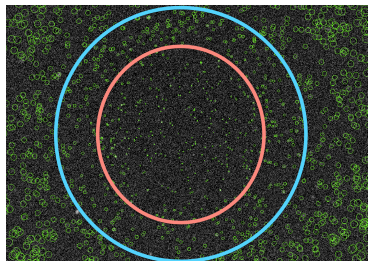
- Model:

- Counts in the pure background:

$$X_k | \xi_k \sim \text{Poisson}(A_k T \xi_k)$$

- Counts in the source region  $s \in \mathcal{R}_k$ :

$$B_s | \xi_k \sim \text{Poisson}(a_s T \xi_k)$$



# Simulation Setting

- Simulation Settings:

$$Y_i \sim \text{Poisson}(\lambda^* + \xi^*), \text{ for } i = 1, \dots, 1000$$

$$\lambda^* \begin{cases} = 0 & \text{with probability } \pi_d, \\ \sim \text{Gamma}[\mu^* = 15, \theta^*] & \text{with probability } 1 - \pi_d. \end{cases}$$

$$X \sim \text{Poisson}(2.5 \times 10^5),$$

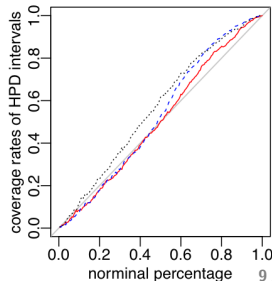
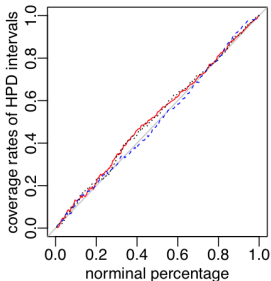
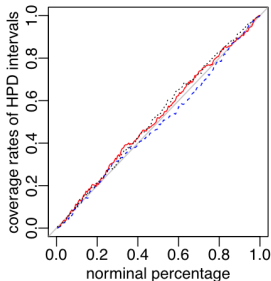
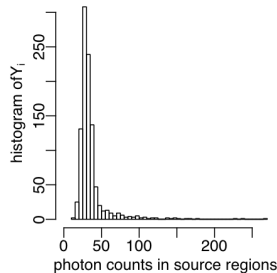
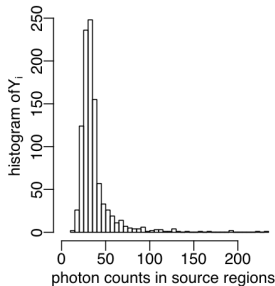
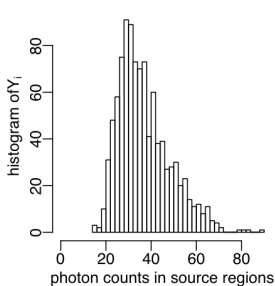
- $\theta^*, \pi_d, \xi^*$  vary at different values:

- $\xi^*$ : 15, 30
- $\theta^*$ : 50, 100, 300, 500, 1000
- $\pi_d$ : 0, 0.1,  $\dots$ , 0.9

- No overlapping sources
- Homogeneous background

# Coverage Rates of 95% HPD Intervals

- $\pi_d = 0.5, \xi^* = 30, \mu^* = 15, \theta^* = 100, 500$  and  $1000$ .



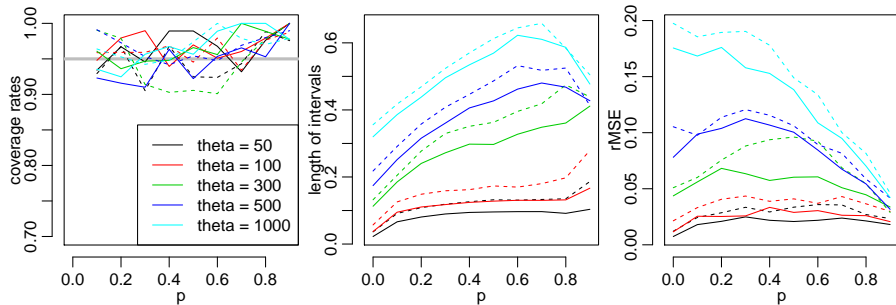
# PME and HPD Intervals Estimates of $\pi_d$

- 100 replicate datasets for each simulation configuration.
- In each cell, the three summaries are (i) coverage rate of 95% HPD intervals, (ii) average length of intervals, (iii) root MSE

$\xi^*$	$\theta^*$	$\pi_d$									
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
15	50	–	93.4%	96.7%	94.6%	98.9%	98.9%	96.8%	93.2%	97.6%	100%
		0.02	0.07	0.08	0.09	0.09	0.1	0.1	0.1	0.09	0.1
		0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	100	–	94.8%	97.9%	99%	93.9%	97%	95.1%	96%	97.9%	100%
		0.04	0.09	0.11	0.12	0.12	0.13	0.13	0.13	0.13	0.17
		0.01	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02
	300	–	96.1%	93.6%	94.7%	94.8%	96.6%	95.6%	100%	98.9%	97.8%
		0.11	0.19	0.24	0.27	0.3	0.3	0.33	0.35	0.36	0.41
		0.04	0.06	0.07	0.06	0.06	0.06	0.06	0.05	0.04	0.03
	500	–	92.3%	91.6%	91%	96.3%	92.2%	95.3%	96.6%	95.3%	100%
		0.17	0.25	0.32	0.36	0.41	0.43	0.46	0.48	0.47	0.43
		0.08	0.1	0.1	0.11	0.11	0.1	0.08	0.07	0.05	0.03
	1000	–	93.5%	92.5%	95.7%	96.7%	95.7%	98.9%	100%	100%	97.8%
		0.32	0.39	0.44	0.5	0.53	0.57	0.62	0.61	0.59	0.48
		0.18	0.17	0.18	0.16	0.15	0.14	0.11	0.09	0.07	0.04

# PME and HPD Intervals Estimates of $\pi_d$

- $\xi^* = 15$  (solid lines);  $\xi^* = 30$  (dashed lines)



# Hypothesis Testing for the Existence of Dark Sources

- Hypothesis Testing:

$$H_0 : \pi_d = 0, \quad H_a : \pi_d > 0.$$

- Reject  $H_0$  if the p-value is low,

$$\text{p-value} = P(T(\mathbb{D}) > T^{obs} | H_0),$$

where  $\mathbb{D} \sim H_0$  and  $T(\mathbb{D})$  is a test statistic.



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$$\lambda_i | \mu, \theta, H_0 \sim \text{Gamma}[\mu, \theta].$$

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- Posterior predictive p-value (*ppp*):

$$\begin{aligned} ppp &= P(T(\mathbb{D}) > T^{obs} | \mathcal{D}^{obs}) \\ &= \int P(T(\mathbb{D}) > T^{obs} | \mu, \theta, \pi_d = 0) P(\mu, \theta | \mathcal{D}^{obs}, \pi_d = 0) d\mu d\theta. \end{aligned}$$

# Hypothesis Testing for Existence of Dark Sources

- Estimation of  $ppp$ :

- 1 Draw  $(\mu^{(t)}, \theta^{(t)})$  from  $P(\mu, \theta | \mathcal{D}^{obs}, \pi_d = 0)$  for  $t = 1, 2, \dots, m$ ,
- 2 For each pair  $(\mu^{(t)}, \theta^{(t)})$ , simulate  $\mathbb{D}^{(t)}$  from the null model and calculate  $T^{(t)} = T(\mathbb{D}^{(t)})$ ,
- 3 Estimate  $ppp$  by

$$ppp \approx \frac{1}{m} \sum_{t=1}^m I(T^{(t)} > T^{obs}).$$

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$$ppp \approx \frac{1}{m} \sum_{t=1}^m I(T^{(t)} > T^{obs}).$$

- Likelihood Ratio Test Statistics:

$$R(\mathbb{D}) = \frac{\sup_{\mu, \theta, \pi_d} L_a(\mu, \theta, \pi_d | \mathbb{D})}{\sup_{\mu, \theta} L_0(\mu, \theta | \mathbb{D})},$$

We use  $T(\mathbb{D}) = \log(R(\mathbb{D}))$  as the test statistic.

## Two simplifications for the LRT:

- To obtain the likelihood  $L_a(\mu, \theta, \pi_d | \mathbb{D})$  or  $L_0(\mu, \theta | \mathbb{D})$ , we need to integrate out all other parameters.

$$P_a(\mathbb{D} | \mu, \theta, \pi_d) = \int P(\mathbb{D} | \xi, \lambda) P(\xi) P_a(\lambda | \mu, \theta, \pi_d) d\lambda d\xi.$$

- No close form likelihoods if some source regions overlap and  $\xi$  is random.

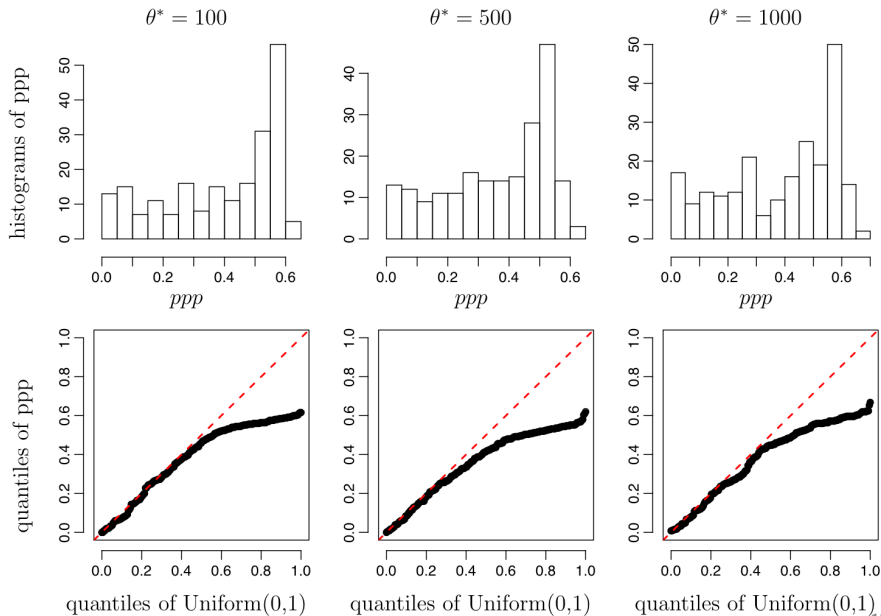
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- No close form likelihoods if some source regions overlap and  $\xi$  is random.
- Two simplifications in the calculation of likelihoods:
  - 1 Simplification 1: Plug in  $A_k \hat{\xi}_k t = X_k$ .
    - Hardly changes the posterior distribution of hyper-parameters!
  - 2 Simplification 2: Likelihoods are calculated based on non-overlapping sources  $\mathbb{D}^*$ :  $L_a(\mu, \theta, \pi_d | \mathbb{D}^*)$  and  $L_0(\mu, \theta | \mathbb{D}^*)$
- $T(\mathbb{D}^*) = \log(R(\mathbb{D}^*))$  is still a valid statistic.

# Simulation Study: Distribution of $ppp$ under $H_0$



# Simulation Study: Power of the Test

Table 3: The rejection rates of our hypothesis testing procedure.

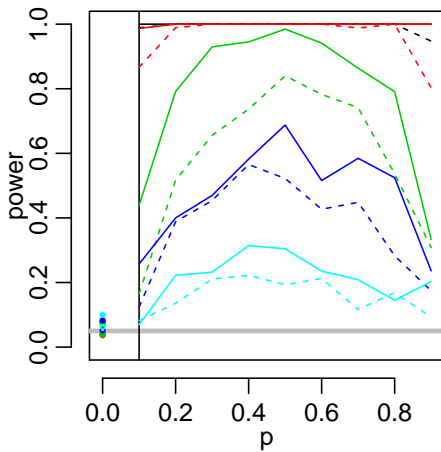
$\xi^*$	$\theta^*$	$\pi_d$									
		0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
15	50	6.8%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	100	3.7%	98.7%	100%	100%	100%	100%	100%	100%	100%	100%
	300	3.9%	43.9%	79.2%	93%	94.5%	98.5%	94.1%	86.4%	79.1%	33.3%
	500	6.3%	25.7%	40%	47%	58.2%	68.8%	51.6%	58.5%	52.5%	23.6%
	1000	6.1%	6.9%	22.2%	23.2%	31.4%	30.4%	23.5%	20.9%	14.5%	20.3%
30	50	4.1%	98.9%	100%	100%	100%	100%	100%	100%	100%	94.7%
	100	7.8%	86.7%	98.9%	100%	100%	100%	100%	98.8%	100%	80.3%
	300	6.9%	16.5%	51.7%	65.6%	73.7%	84%	78.3%	74.1%	53.7%	30.9%
	500	5.2%	12.4%	38.8%	45.4%	56.5%	52.2%	42.7%	44.8%	28.3%	17.4%
	1000	6.2%	8.3%	13.6%	21.1%	22.2%	19.3%	21.2%	11.6%	16.9%	9.3%

\* Based on 100 replications.



# Simulation Study: Power of the Test

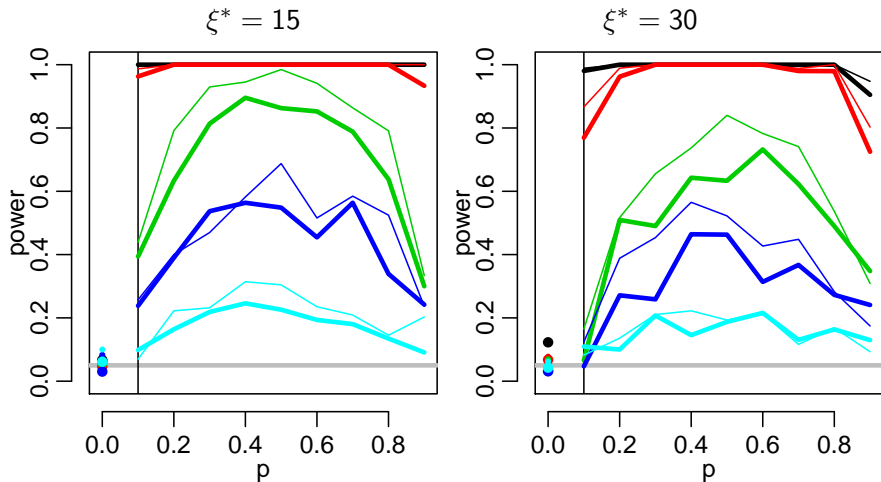
- $\xi^* = 15$  (solid lines);  $\xi^* = 30$  (dashed lines)



\* Based on 100 replications.

# Simulation Study: Power of the Test

- thin lines: all the data are used to calculate the test statistic
- thick lines: 80% of the data are used to calculate  $T$ .

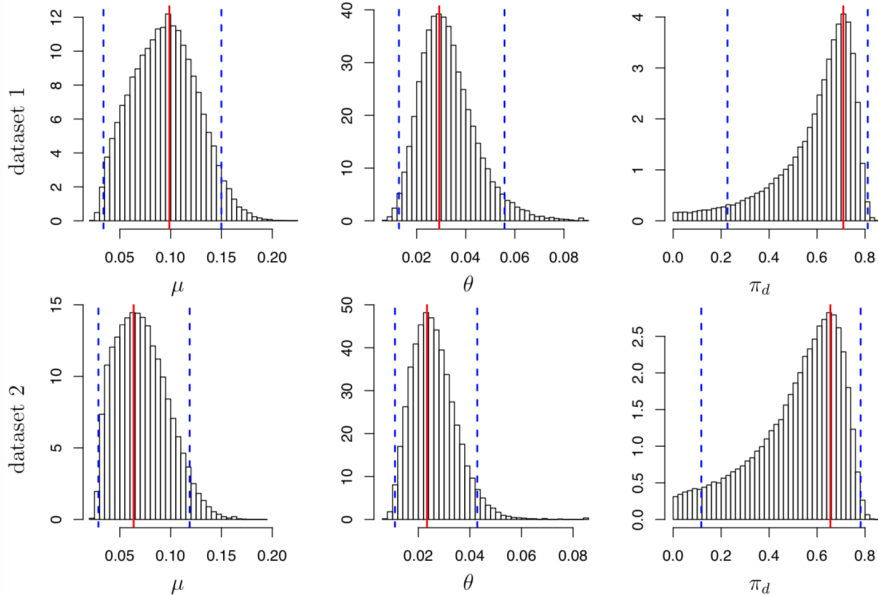


\* Based on 100 replications.

# Real Data: subsets of the Chandra/HRC-I observation of the stellar open cluster, NGC 2516.

- Dataset 1:
  - 649 sources within 6 arcmin from the center of the field
  - 525 non-overlapping sources
  - average source regions  $\approx 1400$  pixels
  - background is assumed to be spatially uniform
- Dataset 2:
  - 1169 sources within 8 arcmin from the center of the field
  - 747 non-overlapping sources
  - average source regions  $\approx 3847$  pixels
  - background is assumed to be piecewise uniform (<6 and 6-8 arcmin)
- data between 6-8 arcmin from the center of the field:
  - 520 source
  - 227 non-overlapping sources
  - average source regions  $\approx 6900$  pixels

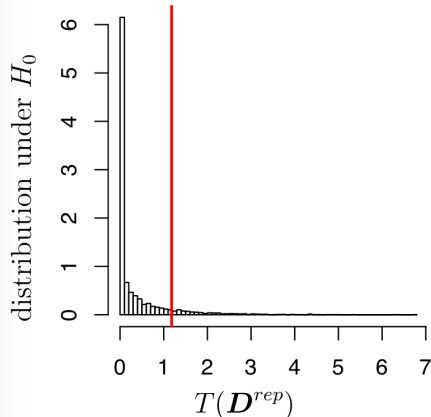
# Real Data Analysis



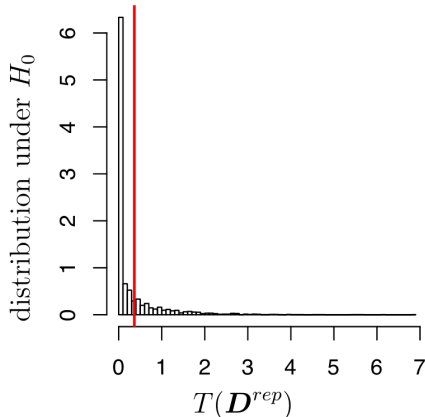
# Real Data Analysis

- Dataset 1:  $T(D^{obs}) = 1.181$  and  $ppp \approx 8.9\%$ .
- Dataset 2:  $T(D^{obs}) = 0.363$  and  $ppp \approx 23.2\%$ .

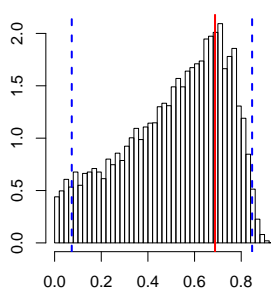
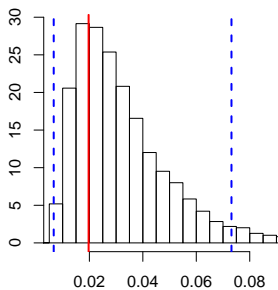
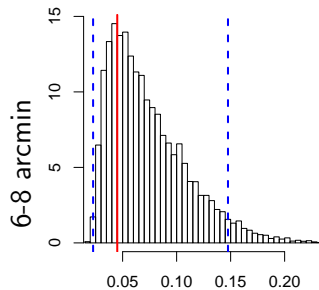
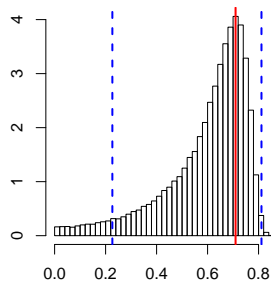
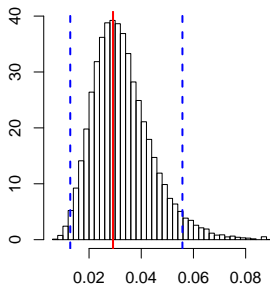
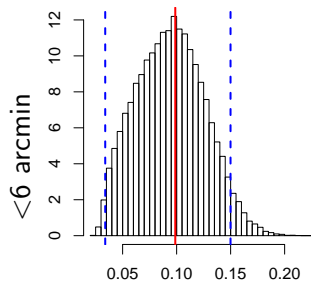
dataset 1



dataset 2



# Real Data Analysis



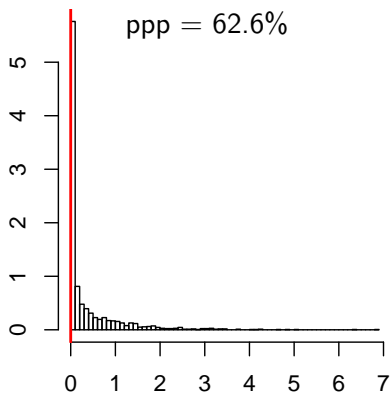
# Real Data Analysis

- If we compute the likelihoods based on the 227 non-overlapping sources between 6-8 arcmin from the center of the field,

$$T^{obs} = 0.$$

MCMC based on Dataset 2

ppp = 62.6%



MCMC based on 6-8 arcmin

ppp = 57.3%

